TOPICAL REPORT
DOE Project DE-FG07-99ID13770

Project Title: Intelligent Automated Nuclear Fuel Pellet Inspection System (Phase-II)
Report period: November 24,1999- May 24, 2000
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Objectives

Quality control in fuel fabrication in the U.S. relies on human inspection of the manufactured fuel pellets before insertion into the zirconium fuel tubes. Generally, the pellets are examined for the following types of defects on their sides: 1) cracks, 2) chips, 3) unusual markings, i.e. water stain, and 4) machine banding. The ends of the pellets are checked for chip defect if edge misalignment is noticed on the pellet-pellet interface when viewing the pellets from the side.

At the present time, pellet inspection is performed by human operators using naked eyes for judgment and decision making on accepting or rejecting a pellet. Fuel pellet inspection is complicated due to the fact that some small degree of chipping or cracking is permissible. Unnecessary re-fabrication of pellets will be costly and too many low quality pellets in a fuel assembly is unacceptable. The current practice of pellet inspection by humans is tedious and subject to inconsistencies and error. In addition, manual inspection is cumbersome since inspectors must keep the pellet at arm's length and wear glasses to protect the lens of the eye. To improve the quality control in nuclear fuel fabrication plant, an automated pellet inspection system based on advanced techniques is needed.

The main objective in this research work is to develop a computerized inspection system to automate the quality control process of nuclear fuel pellet with minimum human operator involvement. This would reduce radiation exposure to the workers, improve accuracy, and maximize productivity and uniformity of the inspection process. The system utilizes video images of the fuel pellets and provides a reliable inspection using artificial intelligent techniques.

A good automated inspection system must go beyond good versus bad pellet identification. This is not acceptable economically because a good/bad pellet inspection system would result in a high rejection rate of otherwise acceptable pellets. The approach in this project is to identify : 1) good versus bad pellet, 2) identify each defect, 3) incorporate the stipulated criteria for each identified defect, and 4) simulate the current manual inspection for pellet end inspection. A decision tree technique will be developed for pellet defect recognition. The results of decision tree will be integrated with the defect criteria data base and an expert system shell to provide a final decision on acceptance or rejection of a pellet.

The first part of this Phase involves the purchase of a video camera and obtaining video images from the ABB fuel manufacturing plant. With respect to the purchase of the camera, it was decided (based on our discussion with the UMR video center) that we first obtain a set of images using the available cameras at the center and test the resulting resolution, then purchase the appropriate camera. The first image acquisition from the ABB plant took place on Tuesday May 16, 2000, using two different video cameras. The result of the preliminary image processing indicates that we need to use a “progressive camera”. An order is in place to purchase such a camera for the second set of data acquisition from ABB.

The results of simulation process as mentioned in the first topical report introduced two challenges for pellet image capturing and analysis: 1) the lighting effect at the pellets-pellet interfaces, and 2) the lack of straight line edge at the pellet boarders. One solution for lighting effect is to utilize polarized lighting and we will explore this during the advanced stage of the project. The challenge associated with the lack of straight line can be overcome by using appropriate techniques for edge detection as explained in this report.

Proper pellet edge recognition is needed so that each pellet could be identified and tagged properly. Template matching of each pellet is done in order to individualize each pellet with an ID tag for defect identification and proper rejection of a defective pellet. Figure 1 shows a conceptual design of video template for ID tagging. This report has two parts, one is the result of simulation using dummy pellets, and the second part is the result of preliminary image analysis of the real pellets from the ABB manufacturing plant.

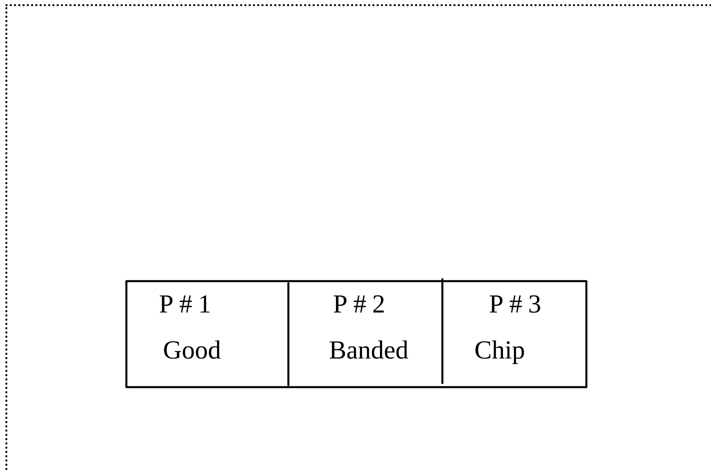

Figure 1. A video template for tagging

Image Acquisition By Simulation

The quality of the image is important for image analysis. There are several parameters that impact the quality of an image: the conditions of the light, the surface condition of the pellet, the distance of the camera, and the gain of the camera.

The reflection and shadow are the most serious problems in the edge detection of the pellets. When the reflection occurs, the shape of the pellet edge will be distorted. Furthermore, the shadow of the pellets will result in producing false edge. In order to get good image for the edge detection, the position and the intensity of the light must be carefully considered. Adjusting the camera and the background can reduce the noise input. Figure 2 shows the laboratory simulated pellet image and the corresponding edge indicating the challenges associated with reflection and shadow.

After the simulation study using dummy pellets, the real pellet images were obtained from the ABB plant. The results of preliminary analysis are described below.

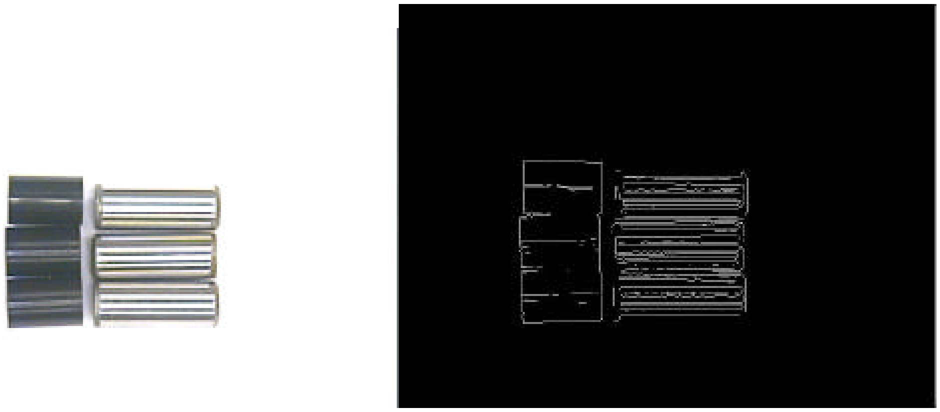

Figure 2. Image and edge of dummy pellets with reflections and shadows

Preliminary Image Enhancement

The images obtained from real pellets are enhanced by intensity adjustment and noise removal. The criteria for the improvement are subjective with the goal of getting a clear image edge at the end. The filtration and thresholding techniques are used to reduce noise and increase the sharpness of the image.

The approach is to sample the image in a regular array of picture elements, filter the sampled image to obtain a low-pass and several band-pass image components, threshold each band-pass image component to remove noise, amplify the thresholded image component to increase sharpness, and add the boosted residual image components to the low-pass image component to obtain a final image for display or processing.

The low-pass image is formed by convoluting the original image array with a 3 by 3 array of weights equal to 1/16 of:

$$\begin{matrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{matrix}$$

Next the high-pass image (contains the edge information) is formed by convoluting the original image with weights equal to 1/16 of:

$$\begin{matrix} -1 & -2 & -1 \\ -2 & 12 & -2 \\ -1 & -2 & -1 \end{matrix}$$

However, the high-pass image can also be obtained by convoluting the original image with each of the eight arrays of weights equal to 1/16 of:

$$\begin{matrix} 0 & 0 & 0 \\ -2 & 2 & 0 \\ 0 & 0 & 0 \end{matrix} \qquad \begin{matrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix} \qquad \begin{matrix} 0 & -2 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{matrix} \qquad \begin{matrix} 0 & 0 & -1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix}$$

(1) (2) (3) (4)

$$\begin{matrix} 0 & 0 & 0 \\ 0 & 2 & -2 \\ 0 & 0 & 0 \end{matrix} \qquad \begin{matrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{matrix} \qquad \begin{matrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & -2 & 0 \end{matrix} \qquad \begin{matrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ -1 & 0 & 0 \end{matrix}$$

(5) (6) (7) (8)

Next, the thresholding technique is applied to the eight components so created to remove noise. Then, each of the eight components are multiplied by a factor greater than unity to increase sharpness, and finally added to the result of the low-pass filtered image to create an enhanced image for processing.

Edge Detection Approach

Edges are curves in the image where rapid changes occur in brightness or in the spatial derivatives of brightness. The changes in brightness that we are particularly interested in are the ones that mirror significant events on the surface being imaged. An edge in an image is a significant local change in the image intensity, usually associated with a discontinuity in either the image intensity or the first derivative of the image intensity. Discontinuities in the image intensity can be either step discontinuities or line discontinuities or both.

In one dimension, a step edge is associated with a local peak in the first derivative. The gradient is a measure of change in a function, and an image can be considered to be an array of samples of some continuous function of image intensity. By analogy, significant changes in the gray values can be detected by using a discrete approximation to the gradient. The gradient is the two-dimensional equivalent of the first derivative and is defined as the vector

$$G[f(x,y)] = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

There are two important properties associated with the gradient: (1) the vector G[f(x,y)] points in the direction of the maximum rate of increase of the function f(x,y), and (2) the magnitude of the gradient, given by

$$G[f(x,y)] = \sqrt{G_x^2 + G_y^2}$$

From vector analysis, the direction of the gradient is defined as:

$$a(x,y) = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$

where, the angle α is measured with respect to the x axis.

Note that the magnitude of the gradient is actually independent of the direction of the edge. Such operators are called isotropic operators.

Three operators, Roberts operator, Sobel operator and Prewitt operator are used here to detect the edge of the image.

Roberts Operator: The Roberts cross operator provides a simple approximation to the gradient magnitude:

$$G[f[i,j]] = \left| f[i,j] - f[i+1,j+1] \right| + \left| f[i+1,j] - f[i,j+1] \right|$$

Using convolution masks, this becomes

$$G[f[i,j]] = |G_x| + |G_y|$$

where the G_x and G_y are calculated using the following masks:

G_x=

1	0
0	-1

G_y=

0	-1
1	0

Sobel Operator: The Sobel operator is the magnitude of the gradient computed by

$$M = \sqrt{s_x^2 + s_y^2},$$

where the partial derivatives are computed by

$$s_x = (a_2 + ca_3 + a_4) - (a_0 + ca_7 + a_6)$$
$$s_y = (a_0 + ca_1 + a_2) - (a_6 + ca_5 + a_4)$$

with constant c=2.

S_x=

-1	0	1
-2	0	2
-1	0	1

S_y=

1	2	1
0	0	0
-1	-2	-1

Note that this operator places an emphasis on pixels that are closer to the center of the mask. The Sobel operator is one of the most commonly used edge detectors.

Prewitt Operator: The Prewitt operator uses the same equations as the Sobel operator, except that the constant c=1. Therefore :

S_x=

-1	0	1
-1	0	1
-1	0	1

S_y=

1	1	1
0	0	0
-1	-1	-1

Note that, unlike the Sobel operator, this operator does not place any emphasis on the pixels that are closer to the center of the masks.

Results and Analysis

Figure 3 shows the video image of five rows of pellets as they are examined visually by naked eye for surface flaw detection.

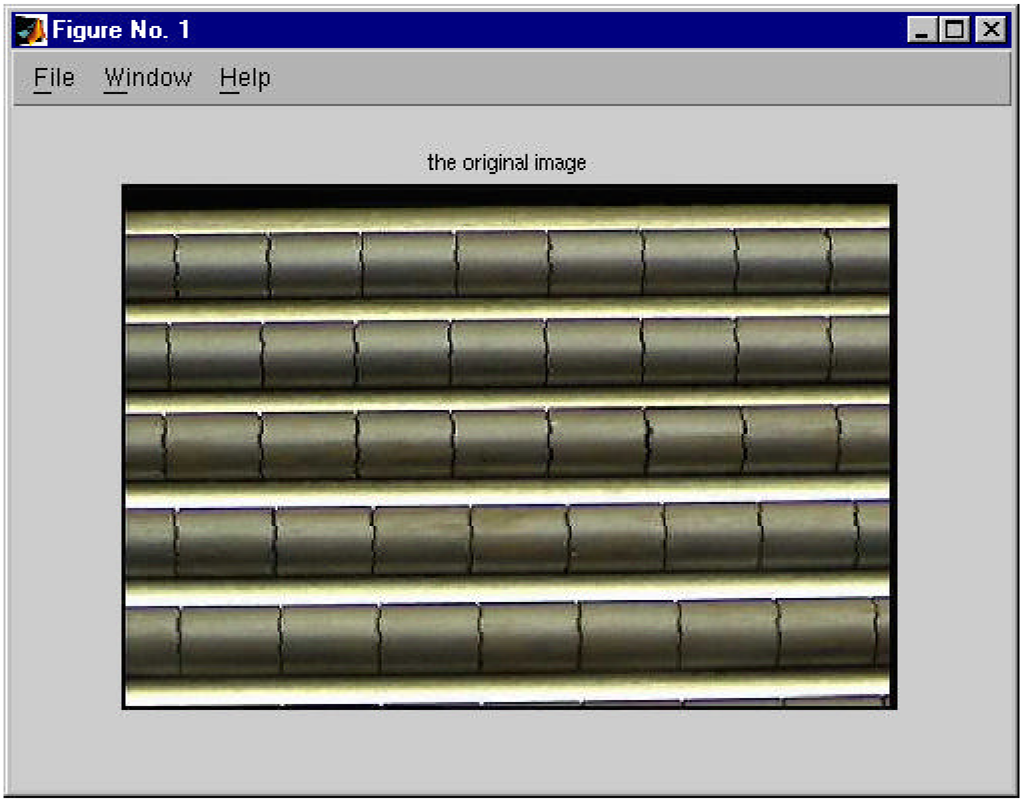

Figure 3. The original image of the pellets

The result of edge detection using Prewitt operator is shown in Figure 4. This Figure shows that using Prewitt operator directly, the edge of the pellets are not clear. Some improvement is possible by using convolution of the low frequency and high frequency filtering of the image. By enhancing the high frequency component, then adding the low frequency and high frequency components, the reconstructed image is created. Now, applying the Prewitt operator to the reconstructed image produces a much more clear pellet edge as shown in Figure 5. Similar results are obtained using Sobel and Roberts operators.

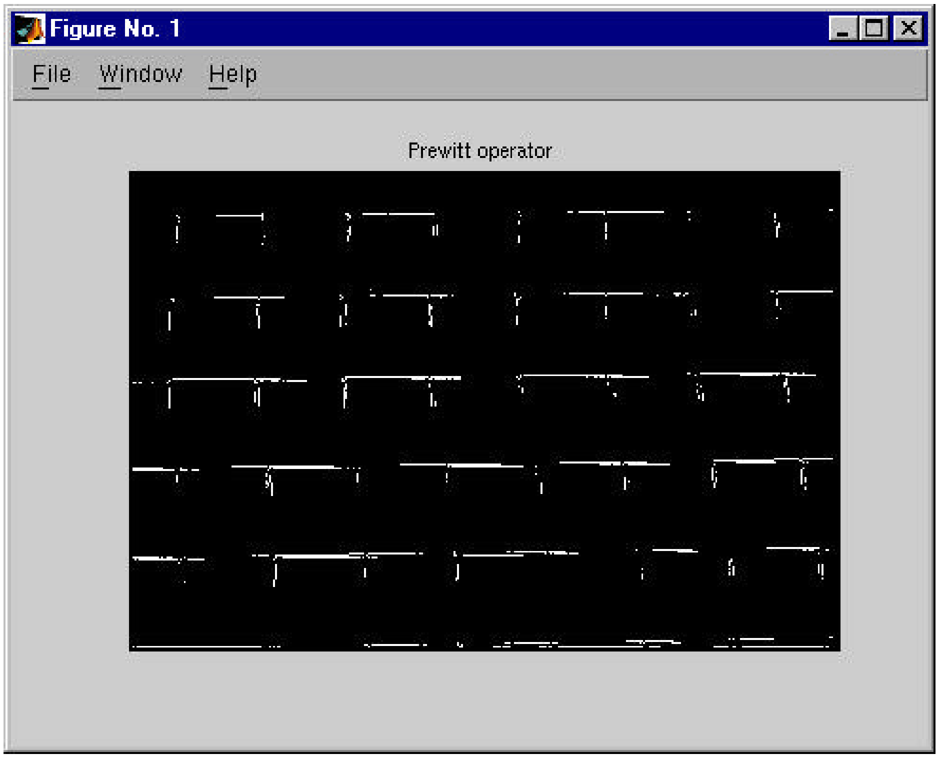

Figure 4. The edge of the pellets using Prewitt operator

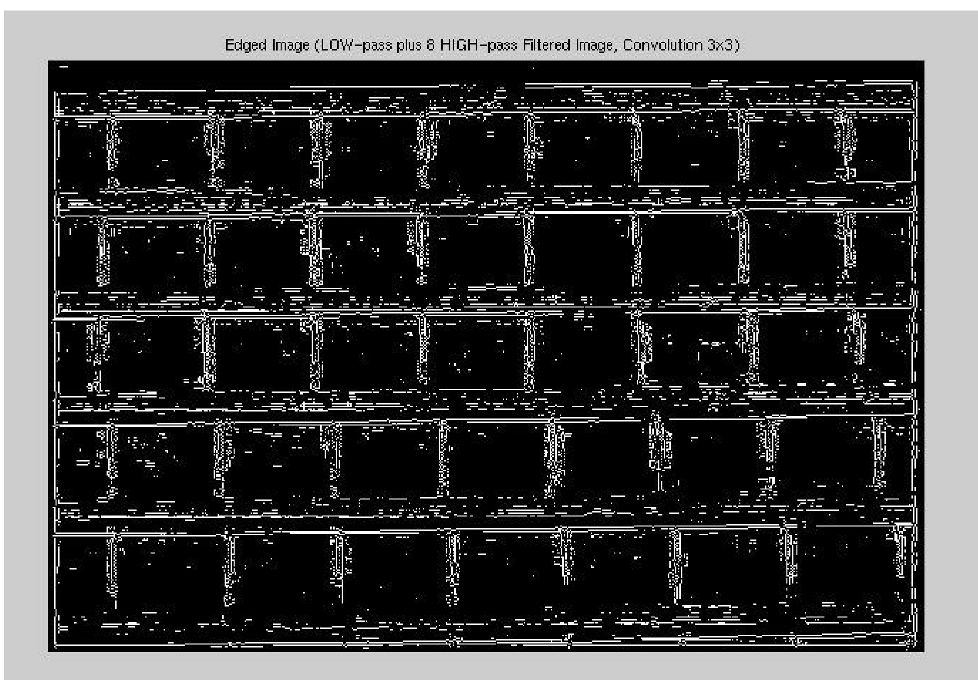

Figure 5. The edge of the reconstructed image by prewitt operator

Results of Edge Detection For One Row Of Pellets

Figure 6 shows a row of three pellets with some shadow at the left. Without the image preprocessing for the noise removal and sharpness, the edge detection result is not good. There are false edges due to the shadow (extra lines at the far left) and reflections (center-line) as shown in Figure 7.

Figure 6.   The original image of three pellets

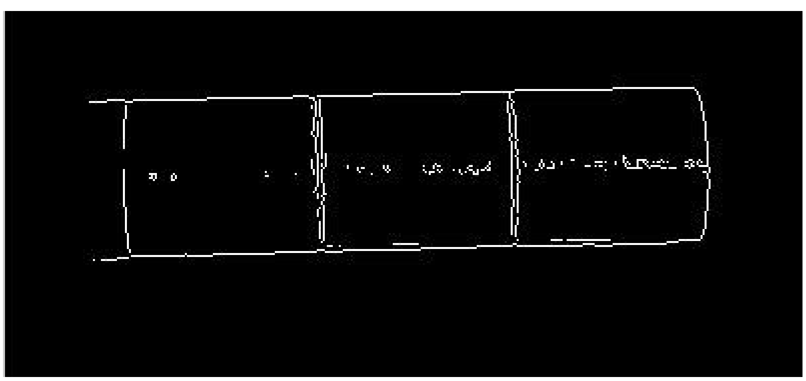

Figure 7. The edge detection result without preprocessing

There is a trade-off between the edge strength and noise reduction. Next, the image is filtered by a low-pass filter and a high-pass filter. The low-pass filter gives the information of the image but decreases the sharpness of the edge. The high-pass filter gives the information on the edges but decreases the image information, hence, adding them together can compromise the trade-off. Figure 8 shows the result of edge detection using this filtering pre-processing of the image and applying the Prewitt operator. It is clear that the shadow effect is removed and even the effect of the reflections are significantly improved.

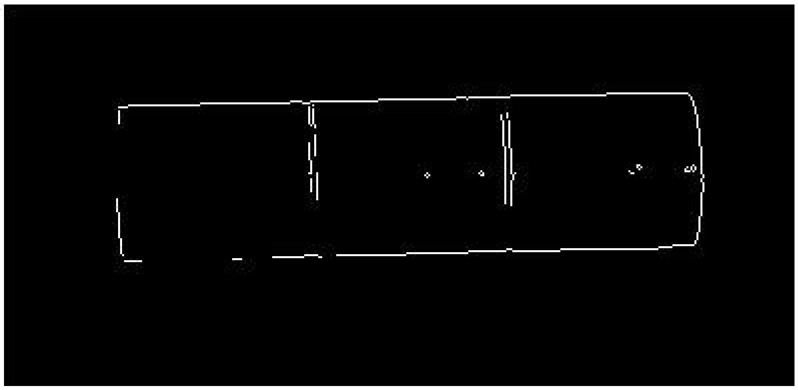

Figure 8. The image edge using low pass and High-pass filter pre-processing together with Prewitt operator

Results show that through the image enhancement good edges of the pellets can be obtained with a good compromise between the edge sharpness and the noise removal.

Work is still in progress and the Phase-I is expected to be completed as scheduled.